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A Sentiment Analysis of Peer to Peer Energy Trading Topics from Twitter

(Full paper)

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ABSTRACT

The emergence of the Peer-to-Peer (P2P) energy trading platforms provides a new method for the general public to use and trade green energy. How to design the peer to peer energy trading platform thus becomes important in facilitating user trading experience. This study will use the data mining method to evaluate factors impacting P2P energy trading experience. Python was used to analyze data extracted from Twitter and Natural Language Processing (NLP) method was implemented with hierarchical Latent Dirichlet Process (hLDA) model. . The study's findings will be examined in detail.

Keywords: Peer to Peer energy trading, data mining, hLDA, feature engineering

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INTRODUCTION

P2P energy trading is a type of Collaborative Consumption (CC) service involving direct energy trading among peers such that local energy prosumers as well as consumers trade small-scale Distributed Energy Resources (DERs) energy in offices, dwellings, and factories (Zhang, Wu, Zhou, Cheng, & Long, 2018). It can be observed that this had a considerable positive impact on the market share of renewable energy (Andoni et al., 2019), balancing energy consumption and generation (Mengelkamp et al., 2018), environmental outcomes (Morstyn, Farrell, Darby, & McCulloch, 2018), and cost saving (Zepter, Lüth, del Granado, & Egging, 2019).) CC can be seen as a type of the sharing economy and occurs either in organized systems or in networks such that participants implement sharing activities such as lending, renting, trading, swapping, and bartering goods, transportation solutions, services, money, or space (Möhlmann, 2015). CC has enabled the transformation of traditional consumption communities from local marketplaces that have restricted economic activity into collaborative global communities that can have significant social, economic, as well as environmental impacts (Perren & Grauerholz, 2015). This, as noted by Heinrichs (2013), can result in a new style of sustainability. Further, Peer-to-Peer (P2P) online platforms aid the CC services' infrastructure while leading to various sectors that have enabled small suppliers to challenge the traditional goods and services providers (Hagiu & Wright, 2015). For example, Airbnb helps in renting a spare room to those who need it and CarNextDoor helps in lending a car. Although various projects including Peer Energy Cloud in Germany and Transactive Grids in US (Park & Yong, 2017) have been encouraged, the applications have not expanded at the expected rate (Bray, Woodman, & Connor, 2018). There are gaps in literatures concerning reasons behind users' participation in such a collaborative activity and factors discouraging users from participating in it. Moreover, not only can the new P2P energy trading, within a short period of time, notably oppose the current energy market structure (Andoni et al., 2019) along with the current experimental projects, but the communication gap between prosumers has been observed to be a major reason impacting the P2P energy trading platform's effective operation (Morstyn, Hredzak, & Agelidis, 2016). Compared with the similarities and differences among different p2p energy projects, many of the trails focus on business models acting similarly to a supplier's role in the electricity sector, it is also necessary to design the necessary communication and control networks that could facilitate P2P energy trading among local Microgrids (Zhang, Wu, Long, & Cheng, 2017). How to design the P2P energy trading platform so that it will provide an optimized user trading experience is thus important for the P2P energy platforms.

The CC literature indicated that factors influencing collaborative consumption platform usage includes community belonging, economic drives, environment impact, technology innovation, and trust (Barnes & Mattsson, 2016; Brown & Venkatesh, 2005; Hamari, Sjöklint, & Ukkonen, 2016). Studies have observed the profile of CC users and the factors impacting their services including studies on Airbnb (Möhlmann, 2015) and car sharing (Bardhi & Eckhardt, 2012). Although P2P energy trading is considered a type of CC, its nature charterers make it slightly different. For example, the frequency of using Airbnb in 2015 was 3.3 times per year (Tussyadiah, 2016) which is far less than the frequency of using energy which is required 24/7. There is a research gap on which factors influencing P2P energy trading. Studies concerning energy consumers' motivations have noted major extrinsic factors including technology innovativeness, economic benefits, and environmental benefits (Langheim, Arreola, & Reese, 2014; Michelsen & Madlener, 2013). As per Roy, Caird, and Abelman (2008), energy prosumers have motivations such as the rising fuel prices, technological cleanliness, and active personal contribution to protecting the environmental. According to Bleicher and Gross (2015), environment-friendly technology as well as economic feasibility are the major contributing factors. Caird and Roy (2011) noted that intrinsic factors such as the pleasure of being the owner of and using environment-friendly technology is important. When the transformation of customers to both producers and consumers, motivations also changed. That is, considering P2P energy trading as a collaborative consumption service can lead to several motivations as prosumers are expected to have their own preferences regarding risk-aversion, financial return, energy securities, as well as environment/social concerns (Darby, 2013).

This present study aims to fill this gap by examining factors impacting P2P energy trading. Hence, the present study will examine the gaps in literature based on the factors influencing using CCs, while noting the differences compared to other CC services including Airbnb. This study also intends to use the Natural Language Processing (NLP) method to assess factors that impact P2P energy trading experience. In particular, the data in this study will be obtained from Twitter and assessed using the NLP method's Hierarchical Latent Dirichlet Process (hLDA) model with python. The study can make theoretical as well as practical contributions in three major ways. First, examining the reasons for energy trading can help resolve the communication problem among customers and prosumers. Second, it may help by offering significant insights for P2P energy trading shareholders and enable better decision-making. Third, the new NLP analytic methods concerning energy trading can offer a new method to evaluate the CC motivations.

LITERATURE REVIEW

The Context Of Peer To Peer Energy Trading

From the late half of 1990s, Europe has completely implemented Information and Communication Technology (ICT) use in distributed power networks, and as noted by Park and Young (2017), it has been expected that, in the future, individuals will be able to exchange the distributed power source generated electricity, thus ensuring the prosumers and consumers' exchange regarding the surplus energy. Moreover, they also suggested that there has been increased encouragement for energy trading platforms on a global scale, including Peer Energy Cloud in Germany, Open Utility in the UK, and Brooklyn microgrids in the US. According to Montemayor, Boersma, & Dorp (2018). Until 2018, there were 143 P2P energy projects in the world, beside of this, the top 3 countries are the Netherlands, Germany and the US. Most of the action (over 64%) is concentrated on the European continent.

P2P energy trading is crucial as it enables customers to transform into prosumers because of DERs technology. Further, as new proactive customers replace the typical passive consumers' traditional identity, it has led to changes in energy power networks that continue evolving. Typically, every country has certain major players in the energy industry that control the centralised power distribution, and because of such centralised conventional energy transition, consumers used to be passive concerning the power network. The introduction of ICT-based smart grid technology, however, enabled substantial amount of data from various sources to be collected and assessed. The data sources include Internet of Things (IoT) devices, sensor networks, and wearable devices (Pieroni et al., 2018) that have allowed two-way communications between prosumers and consumers. As noted by Khan et al. (2013), many researchers have examined this subject by using techniques such as home automation, advanced metering infrastructure (AMI), smart meters, and home area networks (HANs). Such technologies have aided in promoting communication's bidirectional nature which has not only increased the efficiency of energy but also allowed electricity consumption to be better evaluated, planned, used, as well as modified (Parag & Sovacool, 2016). Vehicle owners as well as consumers can re-assess from where they purchase energy and how they use it because of new technologies including vehicle-to-grid electric automobiles and smart meters, be it through trading energy with small-sized and medium-sized agents or directly. Zhou, Wu, and Long (2018) noted that P2P energy trading has a distinct approach in which operators offer a local market platform that has the required functions to ensure that individual benefits are achieved as it helps prosumers trade and share energy with one another. Agents who consume as well generate electricity are prosumers. A major advantage of this framework is that it allows prosumers to gain control over their individual DERs, because of which participation is ensured without motivational incentives. Further, as per Hagiu and Wright (2015), these trading platforms help smaller-scale suppliers in competing with more traditional and larger companies which provide services and goods and have thus emerged in numerous sectors. Hence, it has led to a new power system operation model which is energy trading on microgrids. According to Zhang et al. (2017), this model will help people generate their own energy in domestic settings, offices, and factories through Renewable Energy Sources (RESs) that can also be shared and traded locally in their community.

It should be noted that all P2P energy trading platforms have to address the problem of network's nodes which handles the local supply and demand while considering the energy prices and grid conditions. Moreover, as noted by park and Yong (2017), it is difficult to implement communication between various DERs effectively through energy storage systems (ESS). Morstyn et al. (2018) stated that it is important to combine DERs, control, and consumer communications, but as predicting customer preferences is difficult, P2P energy trading communication also becomes difficult. As per (Zhang et al., 2017), previous studies have focused on business models as well as platforms functioning in a manner similar to the role of a supplier in the electricity sector. On the other hand, local P2P energy trading must have a communicated and controllable network which has a current trading data-based trading network so that it is effective.

The Public Blockchain Platform is a P2P energy trading infrastructure and is largely used in existing trial projects. Its developers describe Blockchain as a distributed ledger which helps individuals conduct transactions with one another without requiring a reliable third party such as a bank. Now, the ledger become numerous models that are applicable to various business problems and can drastically enhance information sharing (Hancock, 2016). For example, the US-based Brooklyn Microgrid that can coordinate DERs for continuing supply in case of the microgrid being separated from the main grid. In such a platform, prosumers tend to be incentivised based on the shared aims, including minimising local pollution, for developing microgrids as well as other community energy initiatives. Such community-based goals help in creating more awareness about P2P energy trading platforms and ensure that local users provide support.

The World Energy Council (2018) noted that it is important to be careful for ensuring that such a balance is sustained when rapidly transitioning to new digital, decentralized, and decarbonized systems because of the risk of trade-offs developing between the priorities that can hinder their critical balance. As per Morstyn et al. (2018), it is important that extant power networks keep ensuring that customers can access affordable energy in a secure and universal manner while transitioning to a zero-carbon emissions model. Boroojeni et al. (2016), however, believes this is difficult as their energy model is primarily dependent on non-renewable fossil fuels. Further, according to Morstyn et al. (2018), using P2P networks for conducting energy trading is important as they can help prosumers establish prices for transactions as well as determine complementary resources and help in service coordination.

In addition, there are regulatory barriers that oppose the P2P energy trading application. Consider the Piclo for example which is a first P2P energy trading project that was established in 2017 in the UK (open Untility, 2015), with all transactions currently mandated to be conducted through a licensed supplier while customers having only one licensed supplier (as with Piclo). Hence, a domestic prosumer such as solar PV cannot sell any additional generation and must either store it on site or sell it through the supplier to the grid. On the other hand, a customer also cannot buy electricity from anyone apart from their sole contracted supplier. Bray (2018) noted that, today when households are able to buy various products from diverse companies, such a ‘supplier hub’ model can be a hindrance.

Motivations To Adopt Peer-To-Peer Energy Trading

It can be helpful to identify factors which determine the P2P energy trading usage intention as it can help understand CC behaviour as well as identify the feasible tasks of enhancing P2P energy trading providers’ service quality (Tussyadiah, 2016). Hence, it is necessary to examine the influential factors concerning P2P energy trading experience for understanding its motivations. According to the self-determination theory, as noted by Deci and Ryan (1985), motivations can be classified into intrinsic and extrinsic. The extrinsic motivation concerns pursuing valued outcomes that differ from the activity, such as reduced cost or increased income. On the other hand, the intrinsic motivation emphasises the advantages of performing an activity, including perceived enjoyment, instead of the outcome. Studies regarding the motivation behind energy consumers showed major extrinsic factors included technology innovativeness, economic benefits, and environmental benefits (Langheim et al., 2014; Michelsen & Madlener, 2013). As noted by Roy et al. (2008), the motivations behind energy prosumers are rising fuel prices, technological cleanliness, and active personal contribution towards protecting the environment. Further, as per Bleicher and Gross (2015), environmentally friendly technology as well as economic feasibility are major contributing factors. Caird and Roy (2011) also stated that intrinsic factor which is the expected pleasure of owning as well as using environment-friendly technology is important.

Following the conceptualization in previous studies of motivations of CC, community belongings is the first factor which previous study always identified. Studies have highlighted the importance of belonging to a community (Närvänen, Kartastenpää, & Kuusela, 2013) because a community is important for participating in sharing actives (Albinsson & Yasanthi Perera, 2012). Further, the CC fulfils consumers’ social needs that include wanting to socialise (Rachel Botsman & Roo Rogers, 2010) as well as a sense of belonging or being included in a community. Previous studies have noted how much sharing economy impacts the social ties’ development or strengthening and the creation or improvement of participants’ sense of community (Rosen, Lafontaine, & Hendrickson, 2011).

The second factor impacting CC motivation is environmental impact. Phipps et al. (2013) noted that enhancing the environmental, economic, and social impacts of consumption can address the existing as well as future generations’ needs. Hamari et al. (2016) also stated that the sustainable activity of collaborative consumption can increase participation.

Another significant factor is economic benefit that can impact CC motivation. Moreover, participating in sharing can be a rational and utility enhancing behaviour in which exclusive goods ownership is replaced by the consumer with a CC service lower cost options (Belk, 2009). Apart from this, reward is also a type of economic benefit that affects CC services use. Both the intrinsic and extrinsic motivations of participation in open source development, and find that a strong extrinsic motivation is the potential future rewards, such as economic benefits (Alexander Hars, 2002).

Further, enjoyment is a significant determining factor behind intrinsically motivated use because the social networking services as well as similar service design that is utilised elsewhere can enhance relatedness (Deci & Ryan, 1985). Santoso and Nelloh (2017) noted that enjoyment can positively impact customer satisfaction as well as be insignificant regarding future intention.

Attitude is another determining factor concerning CC. According to traditional theories regarding consumer behaviour, as noted by Woodside and Lysonski (1989), attitudes are crucial in the decision-making process and can have a considerable impact on consumer behaviour. Attitude refer to a temperament of favourably or unfavourably responding to a person, object, event, or institution (Ajzen, 2005) that can affect such an intention (Ajzen & Fishbein, 1977).

Another factor is technological innovation that impacts CC motivations. One of CC's significant characteristics follows web 2.0 (Belk, 2009). According to studies on innovation theory, people tend to implement an innovative technology when they believe that it offers certain advantages compared to their current methods and when the technology is less complicated (R Botsman & R Rogers, 2010). That is, consumers prefer trying a new service or product if the technological innovation is able to provide more convenience as well as economic benefit.

Perceived Risk is also a major factor that has a negative impact on the purchase intentions of customers. Perceived risk is the extent one's belief of the uncertainty regarding there will be desirable outcomes (O'Leary-Kelly & J. Vokurka, 1998). In terms of the perceived risk in studies on e-commerce, privacy, credibility, and security are the main issues (D. L. Hoffman, T. P. Novak, & M. Peralta, 1999). In the e-commerce industry where goods are permanently sold for money, it is important that the sharing economy property be returned to its owner following a previously established usage and condition period (Belk, 2014). The perceived risk leads to loss of chance of continued use of the services.

Moreover, trust is a significant factor for determining CC. Trust refers to a subjective belief that one party has about the trustee or the prosumers acting in a way that the other party, such as the consumers, expects during an exchange, transaction, or interaction (Gambetta, 1988). According to L. Hoffman, P. Novak, and A. Peralta (1999), lack of trust is a major reasons for individuals not conducting online transactions, while humans are naturally inclined to trust and determine trustworthiness (Wu, Hu, & Wu, 2010).

It has also been observed that reputation is crucial in determining participation in communities as well as other online collaboration activities including information sharing (Hamari et al., 2016). As noted by Alexander Hars (2002), self-marketing as well as reputation building are significant indicators of the possibility of online collaboration.

Consumer and service studies have noted that perceived quality is a major precursor to satisfaction as well as the intention of again using this service (Cronin Jr & Taylor, 1992). Regarding CC, for example, a car sharing service user or accommodation marketplace user may have greater likelihood of using this service again if they have a positive experience with customer service. Further, Möhlmann (2015) noted that service quality is necessary for ensuring satisfaction and that an option of sharing and additional service quality form new components to assess the success of information system (DeLone & McLean, 1992).

Table 1 Overview of service attributes that appeared in previous studies on CCs services

Authors	Community belongings	Reputation	Trust	Service quality	Environment Impact	Economic Benefit	Technology Innovation	Enjoyment	Attitude	Perceived Risk
(Tussyadiah, 2016)	x				x	x		x		
(Hamari et al., 2016)		x			x	x		x	x	
(Möhlmann, 2015)	x		x	x	x	x	x			
(Santoso & Nelloh, 2017)					x	x		x		
(Yang & Ahn, 2016)		x			x	x		x		x
(Guttentag & Smith, 2017)	x			x		x	x			x
(Zervas, Proserpio, & Byers, 2017)			x	x		x				
(Mittendorf & Ostermann, 2017)	x		x							x

METHODOLOGY

In recently research, NLP can automatically determines which entities are being referred to by the text using both natural language processing techniques and analysis of information gleaned from contextual data in the surrounding text based upon input of a text segment (Liang, Koperski, Dhillon, Tusk, & Bhatti, 2013). Meanwhile, the exploration of Topic Models started from the field of natural language processing (NLP) and information retrieval (IR) (Steyvers & Griffiths, 2007). A large amount of unstructured and unlabeled document were represented and clustered with different topics according to the co-occur frequently in the documents (Sun et al., 2016) Topic model are well used in different subjects, such as comparing twitters and traditional social media (Zhao et al., 2011); analyzing user reviewers in tourism (Rossetti, Stella, & Zanker, 2016) and for open ended survey responses (Roberts et al., 2014).

Data Collection

We collected data from Twitter, a social media platform where users can post their opinions or 'tweets'. Twitter has been a valuable and important source for analysing public opinions (Pak & Paroubek, 2010). We have used the keyword "peer to peer energy trading" to extract 3700 sample tweets from 2009 to 2019. The official Twitter API has a limit of 100 tweets per request and it can only allow users to trace back to maximum six days. Therefore, another unofficial tool based on Python, called 'TwitterScraper'(Taspinar & Schuirmann, 2017) was used to collect all related tweets. The data collected consists of ten columns, including 'user', 'full name', 'tweet ID', 'date and time of the tweet', 'tweet URLs', 'likes', 'replies', 'retweets', 'tweet text', and 'html'.

Data Pre-Processing

Only tweet texts were extracted. As we needed to analyse the topics, we only focus on the tweets they posted and removed other variables collected through TwitterScraper, such as likes and retweets.
URLs were removed. Some tweets contain website URLs, such as ' P2P energy trading"the grid will become a market for making many-to-many connections between suppliers and consumers" http://reneweconomy.com.au/2014/building-the-electricity-system-of-the-future-84762'. Scholars believe that URLs in tweets are not helpful for analysing sentiments and thus, we remove all URL links (Pak & Paroubek, 2010).

Tokenisation, stemming, stop words removal and corpus generation. A specialised python package called TweetTokenizer in NLTK (Loper & Bird, 2002) library was used to tokenise the tweet texts. Then, we stem the words using Porter's stemming algorithm (Porter, 1980). We remove all stop words that used for grammar but are not necessary for understanding the meaning of tweets, such as 'that', 'which', 'on', 'in'. We also remove those words (e.g. 'p2p', 'blockchain', 'energi', etc.) occurring in nearly all tweets. The results after the filters mentioned above become the 'corpus' for topic model. (Schütze, Manning, & Raghavan, 2008).

Hierarchical Latent Dirichlet Process.

Latent Dirichlet Process (LDA) was mostly used in the topic model, which includes both unsupervised and supervised topic model to extract potential topics and also provides a generative probabilistic model form the collections of discrete data, for example, the text corpora (Blei, Ng, & Jordan, 2003; Mcauliffe & Blei, 2008). LDA model has been adopted in many fields. For example, Guo, Barnes, and Jia (2017) use LDA on 266,544 online hotel reviews to identify nineteen controllable dimensions, such as park, car and street. The LDA is based on the Bayesian approach as below and it assumes that the words in each text are drawn from a mixture of baskets independently while each basket contains a set of words and the generative process for each tweet, D (Blei et al., 2003). LDA includes different types of variants, such as the Author-Topic Model which is used to address authorship information (Rosen-Zvi, Griffiths, Steyvers, & Smyth, 2004); The Dynamic Topic Model which can analyze the time evolution of topics in large document collections (Blei & Lafferty, 2006); the Relational Topic Models which can summarise the networks among different documents and predict the links among them (Chang & Blei, 2009).

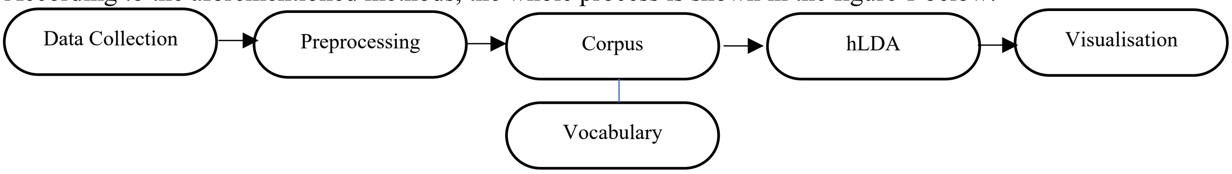
This research employed the Gibbs sampling for the Hierarchical Latent Dirichlet Process (hLDA) to extract the topics and their hierarchical relationships. hLDA is based on the Latent Dirichlet Allocation (LDA) model and a non-parametric prior called the nest Chinese restaurant process (Griffiths, Jordan, Tenenbaum, & Blei, 2004). Griffiths et al. (2004) describe the process as follows:

1) Let c1 be the root restaurant.
2) For each level $l \in \{2,\ldots,L\}$:
   (a) Draw a table from restaurant c_{l-1} using the following 2 equations:
   $$p(occupied\ table\ i \mid previous\ customers) = \frac{m_i}{\gamma + m - 1}$$
   $$p(next\ unoccupied\ table \mid previous\ customers) = \frac{\gamma}{\gamma + m - 1}$$
   Where m_i is the number of previous customers at table i, and γ is a parameter.
   (b) Set c_l to be the restaurant referred to that table.
3) Draw an L-dimensional topic proportion vector θ from Dir(α).
4) For each word $n \in \{1,\ldots,N\}$:
   (a) Draw $z \in \{1,\ldots,L\}$ from Multi(θ).
   (b) Draw w_n from the topic associated with restaurant c_z

Comparing to traditional LDA, hLDA has two main advantages:1. hLDA can explore the hierarchical relationship between topics; 2. Instead of manually choosing the number of topics K in LDA, hLDA can automatically choose the optimal number of topics.

This research used the Python 2 code 'Gibbs sampler for the Hierarchical Latent Dirichlet Allocation' by (Joe, 2017). The results were transformed into structured data and were visualised using Flourish.studio.

According to the aforementioned methods, the whole process is shown in the figure 1 below:



RESULTS AND FINDINGS

Root Topic

A three levels Hierarchical topics model has been developed as per the hLDA. The root topic keywords include 'platform', 'renew', 'solar', 'base', and 'use' and are a total of 5188 words, as shown in figure 2.

Level 1- Subtopics

Considering the hierarchical root topics visualisation illustrated in figure 2, the root topics include 12 subtopics, as presented in table 2.

Table2: 12 level 1 subtopics

Number	Topic	Total words
1.	Solar, trial, Australia, microgrid, news	877
2.	World, enable, help, become, platform	800
3	Deploy interest, present, residences, exchange	758
4	Start up, via, storage, electricity	543
5	Ucl, model, present, group, balancing	500
6	Think, live, help, commodity	453
7	Aim, take, new ,recent, model	354
8	Network,microgrids,excitement, sustain,	307
9	Panel, want, suncontract, larger, retail,	266
10	Chain, system, made, Brooklyn, account	120
11	Explore, chance, point, even, another	105
12	Good, meter, unit, bitcoin	84

Level 3-Subtopics

In topic 1, the third level subtopics with the highest frequency include project set up (261), news, blockchain technology (41), Initial Coin Offering (ICO, 61), and coin payment (figure 3). It also included four countries: Australia, Ireland, Thailand, and Singapore.
In topic 2, the third level subtopics with the highest frequency include fuel, source (261) ICO, wind, electric, wholesale, price, New Zealand (42), marketplace (194), and licences (5) (figure 4).
In topic 3, the third level subtopics with the highest frequency include first system, Britain (12), Chicago(218) social house, friends, family, multifamily (12), interact, buy(11), neighbour, cost, community(22), and fixability (14) (figure 5).
In topic 4, the third level subtopics with the highest frequency include clean (139) product, better (87), plant, reduce emission (82) understand, virtual, and demand (11) (figure 6).
In topic 5, the third level subtopics with the highest frequency include Ethereum (86), tokenpost, power token (23), energy coin (9), and altcoin (31) (figure 7).
In topic 6, the third level subtopics with the highest frequency include need, participants (65), traditional, government (19), licence (19), and permit (8) (figure 8).

Thus, the previous section has presented the hLDA model's top six topics as well as every topic's mean sentiment polarity score. The results show that when people on Twitter discussed energy trading, they largely presented ten types of information, as given below.

1. Countries:
   As stated in topics 1 and 2, the majority of countries included are developed countries, such as the UK, Australia, and New Zealand. As mentioned in the literatures, 79% of current P2P energy projects
2. Trial stage:
   The P2P energy trading project still on the trial stage.
3. News:

P2P energy projects news and the ICO news are the majority of the keywords included in topics 2 and 5 with news. Thus, on Twitter, the majority of the resources on Twitter are news and most discussion on this subject concern the energy coins' ICO.

4. Communities:
   Topic 3 includes communities and neighbourhood that is also affirmed by Zhang et al. (2017). This also shows that P2P's original aim is to help local communities as well as neighbours in selling and exchanging their energy.
5. Environmental benefit:
   Included in topics 2 and 4, helping reduce emission was energy sources represent what kind of source will be delivered in the trading progress, might be solar or another kind of renewable energy. It is, therefore, necessary to take into account whether the diversity of energy sources should be included as a feature in P2P energy trading system. Though more options can create more difficulties when making decisions, assessing this feature can also be helpful for future application.
6. Economic benefit:
   Included in topics 2 and 3, P2P energy trading platform ensures that the energy trading is more flexible and decreases its reliance on the traditional energy networks. Various platforms, however, have different price strategies and P2P energy trading results in challenges for the existing energy marketplace.
7. Blockchain technology:
   As noted in topic 1, block has significantly high frequency because of the existing blockchain projects, including Powerpeers. On the other hand, due to some the data are from the news which discussed Brooklyn microgrids a lot, which is the first peer to peer energy trading project in the world.
8. Payment and energy coins:
   As per topic 5, the determinates concerning payments are included in (Lee & Kozar, 2006; Rose, Hair, & Clark, 2011). This, future P2P energy trading project must take into account implementing tokens as a rational currency concerning the final payment. On the other hand, the trust issue and risk must also be considered because the public continues to be worried about the news payment using energy or environment coins and replacing typical bank payment.
9. Adequate product information:
   As noted in topic 4, lack of sufficient information can result in unfamiliar services and platforms that can hinder customers from using it in the future.
10. Regulation and network constraints:
    As stated in topic 6, P2P energy trading regulations continue to be a constrain regarding the development of platform. Bray (2018) noted that all transactions at present have to be conducted by a licensed supplier and that customers are only allowed to have one licensed supplier (as with Piclo).

As opposed to CC studies, the present study's results do not include reputation and enjoyment. On one hand, this is due to the data sources, most of the twitters are sent from the experts and lack of enough customers. However, as the majority of these projects remain in the trail stage, it leads to small data concerning the project feedbacks and reviews. Moreover, the high frequency of using one's own energy has led to customers not considering reputation or enjoyments and focusing more on economic benefit, environmental benefit, and payment.

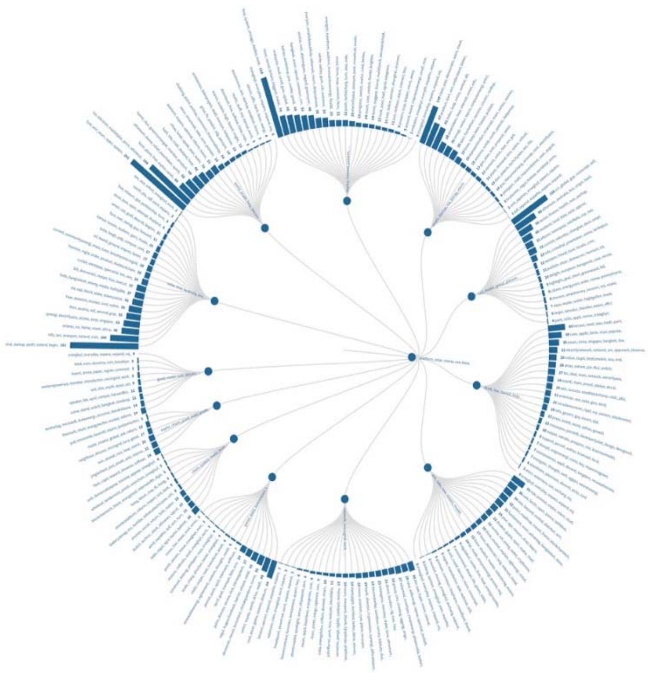


Figure 2. Visualisation of the hierarchical root topics

Figure 3: Subtopics 1, Solar, Australia, microgrids, trial, news

Figure 4:Subtopic2, World, enable, help, become, platform

Figure 5: Subtopic 3, Deploy interest, present, residences, exchange

Figure 6: Subtopic 4, Start up, via, storage, electricity

Figure 7: Subtopic 5, UCl, model, present, group, balancing

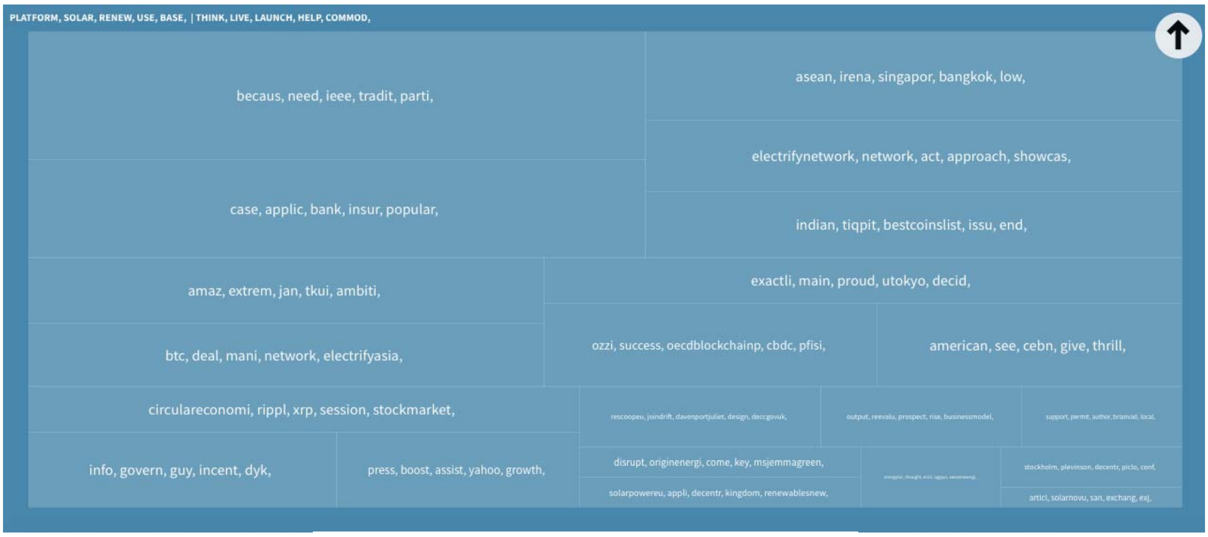


Figure 8: subtopic 6, Think, live, help, commodity

CONCLUSION AND FUTURE WORK

This study aims to present a thorough and enhanced model for examining public attitudes toward P2P energy trading. In this study, all posts that included ‘P2P energy trading’ and ‘energy trading’ were gathered from the social media website, Twitter, and implemented to Hierarchy Latent Dirichlet Allocation for obtaining the major topics. The algorithm resulted in 12 topics considering all tweets. According to the results, the public focused more on the new technology and on the way in which the payment using energy coins works in the trading process. Though there are problems of trust and risk, the focus is more on payment processing. Services that are not traditional CC services, such as Airbnb, enjoyments, and reputations, however, are not included in this study. This suggest energy as a CC is an exception which is a good explain to the traditional literatures.

Though the hLDA model concerning feature engineering is a significant technique to understand the reasons for P2P energy trading, future study should compare two approaches, including Short Text Topic Modelling (STTM). Moreover, the hLDA model results suggests the professionals as well as experts' opinions as they are the ones primarily contributing to the P2P energy trading discussion. Although this can act as the study's limitation, it can also help in interviewing customers with previous trading experience to gain additional information, which is also the future approach of this study.

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